Handheld interventional ultrasound/photoacoustic puncture needle navigation based on deep learning segmentation: supplement

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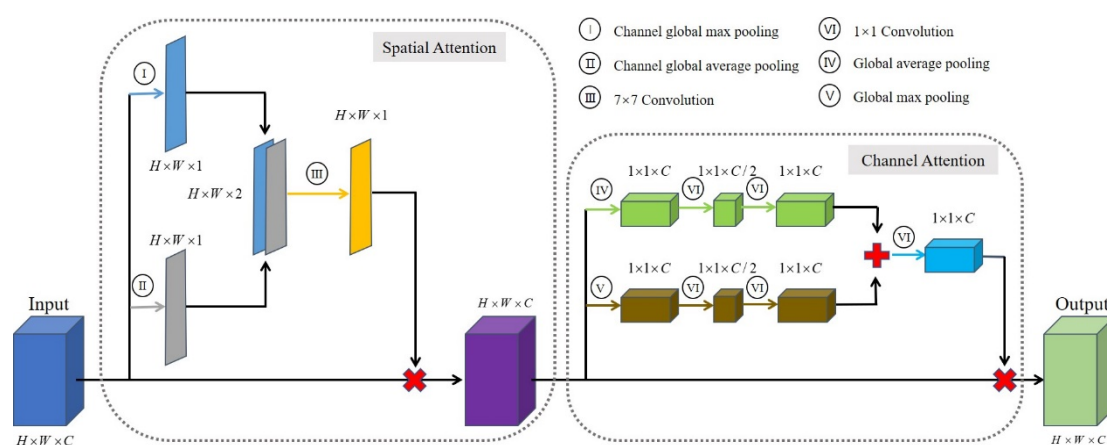** lin_xiangwei@yeah.net, *mian.chen@szu.edu.cn*

Fig. S1. Attention gate mechanism in the U-Net++ architecture.

Explanation to Fig. S1: In the spatial attention module, the input feature tensor was first concatenated through global average pooling and global maximum pooling on the channel, followed by a 7×7 convolution and the sigmoid activation function to get a weight graph with one channel. After multiplying the weight graph with the original input tensor, a characteristic tensor was finally output. In the channel attention module, the feature tensor output by the spatial attention module was first obtained through global average pooling and global maximum pooling to obtain two feature weight sequences. Then these two weight sequences were added after one convolution and sigmoid activation function. Multiplying the weight sequence with the output of the spatial attention module, finally the feature tensor of the same type as the feature tensor of the spatial attention module was obtained.
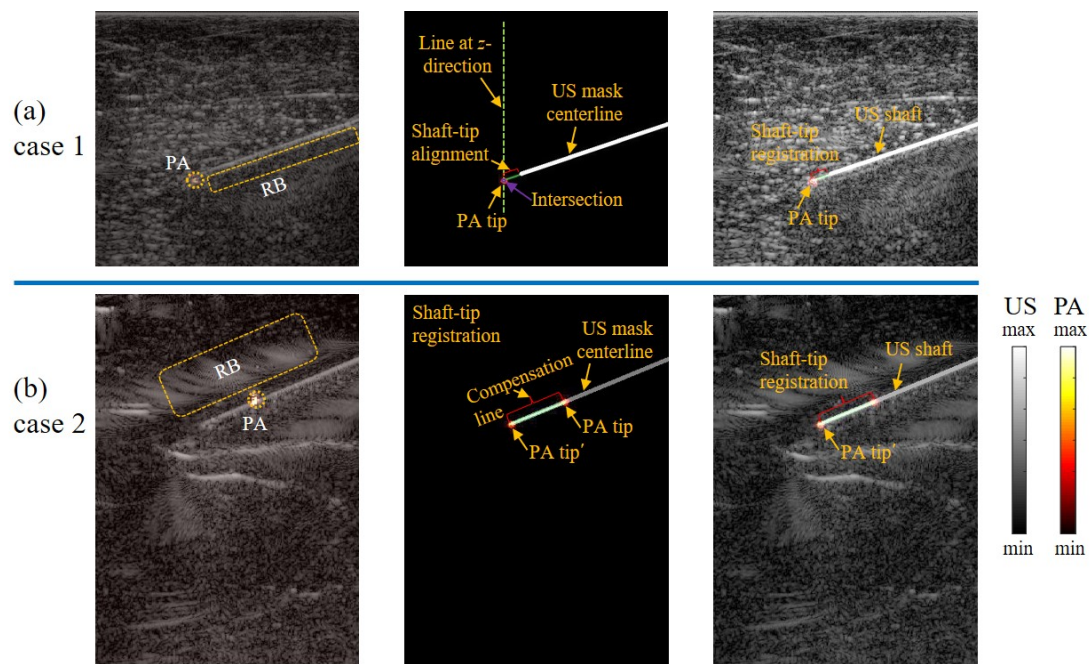
Fig. S2. Dual-modality needle shaft-tip compensation in the representative cases.